Distributional Effects of Residential Solar Subsidies

Ozgen Kiribrahim Sarikaya Yueming Lucy Qiu

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Abstract

The residential solar market has grown significantly in the past decade due partly to falling prices and government subsidies. However, this growth has been driven by high-income households, leading to inequality in the distribution of subsidies. In this paper, we investigate how household income affects demand for residential solar systems and the distributional effects of renewable energy tax credit policies. We estimate a dynamic model of solar adoption using novel household-level data on hourly energy consumption, prices, household income, and solar panel installation for utility company customers in the Phoenix, AZ, metropolitan area from 2013 to 2017. We find that the household's sensitivity to the system cost decreases as income increases. While low-income households are more sensitive to reductions in the system cost, high-income households are more likely to receive the full benefit of a non-refundable tax credit due to their higher tax liability. Specifically, making the tax credit refundable would increase the take-up rate among low-income households by 16%, with no effect on high-income households. Finally, our counterfactual analysis demonstrates that targeted policies designed to allocate 40% of total benefits to lower-income groups can enhance equity in solar adoption while increasing total solar production by 2% compared to nonrefundable policies. Our findings highlight the importance of designing subsidy programs that effectively balance distributional equity and overall efficiency.

Corresponding authors. Emails: okiribra@asu.edu Department of Economics, Arizona State University, yqiu16@umd.edu, School of Public Policy, University of Maryland, College Park.
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1 Introduction

Over the past decade, the residential solar market has grown significantly due partly to falling prices and government subsidies. However, this growth has been driven by high-income households, leading to inequality in the distribution of subsidies. Barbose et al. (2021) report that the median solar adopter's income was $113k/year in 2019, compared to a U.S. median of about $64k/year. Additionally, solar adopters have higher credit scores, more education, and live in higher-value homes. Borenstein and Davis (2016) further document that the bottom three income quintiles have received about 10% of all credits, while the top quintile has received about 60%. To address these disparities, the Biden administration introduced the *Justice40* Initiative, which aims to deliver at least 40% of the benefits from federal investments in clean energy to disadvantaged communities.[1]

In this paper, we develop and estimate a dynamic model of consumer demand for residential solar systems to examine how household income influences the demand for residential solar systems and the distributional impacts of federal tax credit policies in Arizona. In the model, each household solves an optimal stopping problem each year to decide whether to adopt a solar system or to wait and have the option to install it in later years, as in Rust (1987). The dynamic feature of the decision comes from the decline in the uncertain future cost of residential PV systems and the change in incentive policies. Households can wait to get benefits from the expected decline in the upfront cost of systems, and the opportunity cost of waiting is the savings from system electricity generation. The model assumes that households are forward-looking and form rational expectations regarding the evolution of solar technology costs. Additionally, we assume that households have perfect foresight about changes in electricity prices and incentive programs.

We recover the structural parameters in the model using a nested-fixed point algorithm, following Rust (1987). The model evaluates the effect of the cost of adoption, household income, tax credits, and savings from system electricity generation on preferences for rooftop solar systems.

Our analysis relies on a novel household-level dataset compiled from two primary sources. The first dataset comes from the Salt River Project (SRP), an electrical utility that conducted the Residential Equipment and Technology (RET) survey in the Phoenix metropolitan area

[1] Justice40 Initiative.

in 2014. The survey provides detailed household-level information, including income, ethnicity of the household head, and household size, as well as building attributes and appliances such as square footage for both solar and non-solar customers. SRP also provides linked data on electricity usage for surveyed households between 2013 and 2017. For solar customers, the data includes additional information such as daily electricity generated by solar systems, installation dates, adoption costs, and system sizes. These data reveal that higher-income households are more likely to adopt solar systems, live in single-family homes, and consume more electricity from the grid daily on average.

The second dataset is the Distributed Solar Public Data from Lawrence Berkeley National Laboratory's Tracking the Sun 2020 Database. This dataset provides project-level information on residential photovoltaic systems across the U.S., including total installed system price, installation date, system size, zip code, customer segment, and system features.

The estimated coefficients show that households' sensitivity to the cost of adoption decreases as household income increases. We also find that a \$1 increase in the savings from the system weighs slightly more than a \$1 decrease in the net cost of adoption. The model predicts untargeted and targeted moments very well. We then use the model to conduct two counterfactual analyses while maintaining the ex-ante budget equivalent at the benchmark level. The benchmark policy is a non-refundable federal tax credit scheme, which provides 30% of installation costs as a non-refundable tax credit. In the first counterfactual, we modify the scheme to make the tax credit refundable, allowing us to evaluate how the refundability of tax credits impacts the distribution of benefits among households. The second counterfactual examines an alternative refundable tax credit subsidy scheme inspired by the *Justice40* initiative. This scheme is designed to allocate 40% of the total benefits to households with incomes below \$50,000.

Our findings show that making nonrefundable tax credits refundable substantially increases the solar adoption rate among low-income households, with no notable changes in adoption for higher-income groups ($> \$75K$). The adoption rate increases most significantly for households earning less than \$25K, with a rise of 16.4%, followed by smaller gains for the \$25K–\$50K and \$50K–\$75K groups, at 2.8% and 0.7%, respectively. These findings demonstrate that low-income households are unable to fully benefit from nonrefundable tax credit policies due to their low tax liability. Implementing such policies can contribute to solar adoption inequities between high- and low-income households.

Similarly, the total tax credits received by low-income households increase by 47%. This change is driven by two factors: first, households already adopting solar systems now receive higher benefits; second, marginal households changed their decision to adopt a system because the tax credit made it more financially viable. The change in marginal households among low-income groups is reflected in the increase in solar production by 17.9%. Overall, transitioning from a nonrefundable to a refundable tax credit policy increases total solar production by 102.2%.

In the second counterfactual analysis, we aim to allocate 40% of the total benefits to households with incomes below $50,000, inspired by the *Justice40* Initiative. In this case, the total tax credits received by low-income households increase by 168.4% at a cost to higher-income households. The total tax credits received by households with incomes between $75K and $100K decrease by 16.4%, while those with incomes above $100K experience a reduction of 20.3%. Although solar production declines by 3.75% for households earning between $75,000 and $100,000, and by 4.45% for those earning between $100,000 and $150,000, it increases by 40% for low-income households. This substantial increase is sufficient to maintain total solar production at the same level as the refundable tax credit scenario while still showing an improvement compared to the benchmark case.

The main mechanism behind these findings is that high-income households are less responsive to changes in net cost. As a result, even when net costs increase, only a small fraction of them alter their solar adoption decisions. In contrast, low-income households are highly sensitive to the net cost of the system. Therefore, a decrease in net cost incentivizes marginal households to adopt the system. Our results show that the *Justice40* Initiative can achieve a more pronounced redistribution of benefits toward lower-income households without compromising efficiency.

Our paper contributes to two strands of the literature. First, it relates to the growing body of research on estimating demand for residential solar PV systems. Several studies use reduced-form approaches to estimate the elasticity of demand for residential solar systems (Hughes and Podolefsky (2015); Gillingham and Tsvetanov (2019)). Additionally, other studies employ dynamic discrete choice models to analyze the demand for residential solar PV systems and the design and effectiveness of subsidy programs for rooftop solar systems (e.g., Langer and Lemoine (2018); Reddix (2015); Snashall-Woodhams (2019); Burr (2016); De Groote and Verboven (2019)). The most closely related paper is Feger et al. (2021), which estimates a structural model of solar panel adoption using a dataset that includes detailed information on households' socioeconomic characteristics, such as wealth, building attributes, and energy consumption, in

Switzerland from 2008 to 2014.

Relative to the existing literature, this paper is the first to use household-level data to estimate the demand for solar systems in Arizona, with a focus on the heterogeneous effects of adoption costs across household income levels in the U.S. rooftop solar market. Additionally, dynamic models require detailed information about the expected system size, adoption costs, and savings from system electricity generation for non-solar homes. We leverage rich household-level data to improve the precision of these measures, advancing beyond prior studies that primarily focus on the U.S. solar market.[2]

Second, we contribute to the growing literature on the determinants of PV adoption and the socioeconomic heterogeneity of solar adopters (De Groote et al. (2016); Crago and Chernyakhovskiy (2017); Bollinger and Gillingham (2012); Lukanov and Krieger (2019); Kwan (2012)). Borenstein (2017) examines the income distribution of solar adopters and how it has evolved over time, finding that the distribution remains highly skewed toward wealthy households. Similarly, Borenstein and Davis (2016) focuses on the distributional impacts of U.S. federal clean energy tax credits, concluding that higher-income households have predominantly benefited from these incentives. Furthermore, Crandall-Hollick and Sherlock (2014) and Neveu and Sherlock (2016) discuss how higher-income taxpayers are more likely to benefit from residential energy-efficiency tax incentives. They argue that tax incentives may not be the most effective policy tool if high upfront costs are a significant barrier for low- and moderate-income households—who are often credit-constrained.

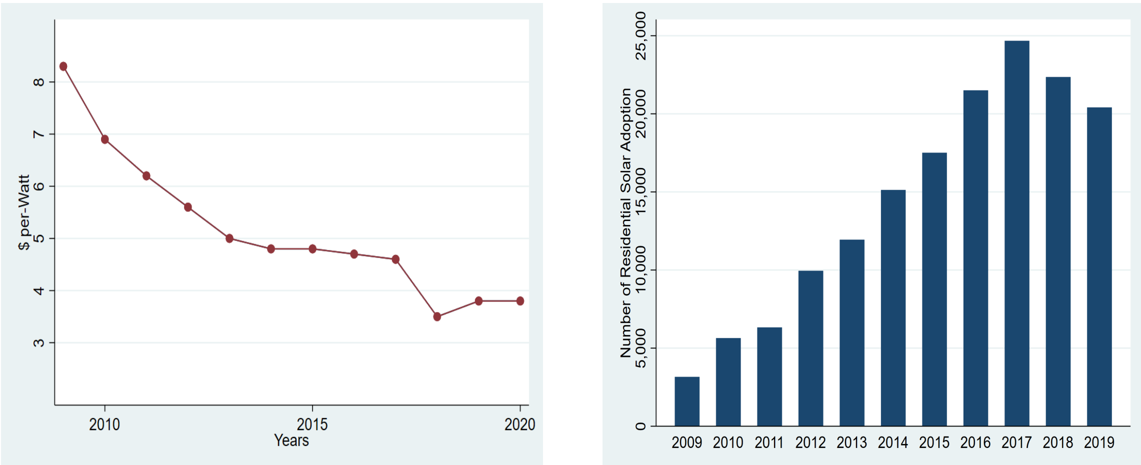
Our second contribution to the literature is to develop a framework for quantifying the distributional effects of current nonrefundable tax credit policies in Arizona. This paper shows how non-refundable policies can contribute to solar adoption inequities between high- and low-income households. Moreover, we demonstrate that transitioning to refundable tax credit policies can significantly increase adoption rates among low-income households without affecting high-income households. Using counterfactual analyses, we quantify how targeted policies, such as allocating a greater share of subsidies to lower-income groups, can enhance equity in solar adoption while maintaining or even increasing total solar production. These findings highlight the importance of designing subsidy programs that balance distributional equity with overall efficiency.

[2] For example, Burr (2016) and Langer and Lemoine (2018) use zip-code level data on average or median system sizes to construct the value of adoption for non-solar homes.

2 Background

Arizona, one of the sunniest states, was ranked as the 5^{th} highest in solar energy generation, with 8% of its electricity coming from solar power by 2020.[3] At the same time, the total solar investment in the state amounted to $14.6 billion.[4] Over the past decade, the price of rooftop solar panels in Arizona has steadily declined. The left panel of Figure 1 illustrates the median installed price per Watt, which dropped from $8.3 in 2009 to $4.8 in 2014, before reaching $3.8 per Watt in 2020. Moreover, the right panel of Figure 1 depicts a rapid increase in solar adopters during the same period.

Figure 1: Cost of Solar Systems and Number of Solar Adopters in Arizona (2009–2020)



The left panel shows the median installed price per watt in Arizona from 2009 to 2020, while the right panel depicts the number of residential solar adoptions in Arizona from 2009 to 2019.
Source: Lawrence Berkeley National Lab, Tracking the Sun Report.

However, the income distribution of solar adopters in Arizona remains skewed toward higher-income households. Figure 2 illustrates the percentage of solar adopters in Arizona by household income, expressed as a percentage of the area median income. Notably, 77% of residential PV adopters have household incomes exceeding 80% of the area median income.

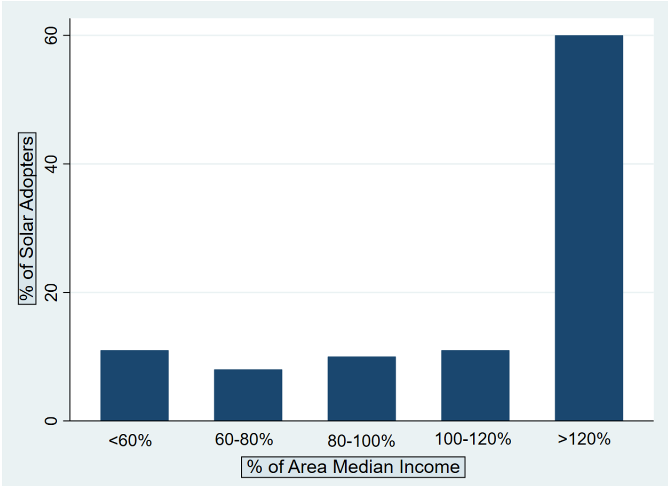
Incentive Programs in Arizona

Several incentive programs were in effect during the sample period in Arizona.

Residential Renewable Energy Tax Credit: The federal tax credit for solar systems on residential and commercial properties was introduced by The Energy Policy Act of 2005. Since then, there have been several changes to the tax credit's terms. Initially, taxpayers could claim

[3]U.S. EIA, Electricity Data Browser, Net generation for all sectors, Arizona Annual, 2001–2020.
[4]Solar Energy Industries Association.

Figure 2: Distribution of Solar Adopters over Income Categories



The figure shows the percentage of solar adopters in Arizona by household income, expressed as a percentage of the area median income. Source: Lawrence Berkeley National Lab, Tracking the Sun Report.

30% of their investment in solar property as a federal tax credit, capped at a maximum of $2,000. This version of the credit was implemented for two years. The Energy Improvement and Extension Act of 2008 later removed the cap and extended the credit for eight years, until December 31, 2016. Subsequently, the federal tax credit was further extended until 2023, with a step-down schedule.

Residential Solar and Wind Energy Systems Tax Credit: Arizona taxpayers who install a solar system have been eligible for Arizona's Solar Energy Credit since 1995. This incentive allows taxpayers to claim 25% of the cost of the system, capped at $1,000. If the taxpayer's liability is less than the credit amount in the year of installation, the remaining portion of the credit can be carried forward and claimed for up to five subsequent years.

Net Billing: Under the net billing system, customers pay only for their net energy usage from the grid. They receive credits for any excess energy generated by their system, which is delivered back to the grid at a fixed price. Customers are billed for the difference between their energy usage from the grid and the credited amount.

Solar and Wind Equipment Sales Tax Exemption: Since 1997, the state has provided a 100% sales tax exemption for the retail sale of solar systems and their installation by contractors.

Energy Equipment Property Tax Exemption: Since 2006, the state has offered a 100% property tax exemption for the increased value of a property resulting from the installation of solar systems. This paper focuses on tax credit policies and accounts for the net billing policy.

3 Model

In this section, we develop a dynamic discrete choice model of residential photovoltaic system (PV) adoption, building on Rust (1987) and Burr (2016). The model assumes that each household has an infinite horizon and discounts future utility at a rate $\beta \in (0, 1)$. In each period t, a household that has not yet adopted a PV system may either choose to adopt a system or postpone adoption and stay with their existing setup. If a household decides to adopt the system, which is a terminating action, the household exits the market. In the case of not adopting, the household retains the option to adopt the system at a later period. In other words, the household chooses not only whether or not to install the system but also when to install it. Thus, the model represents a single-agent optimal stopping problem, as described in Rust (1987).

At the beginning of each period, households in the market have full information about the current period's state space. The state space observed by both households and the econometricians includes the cost of a residential PV system, C_t, the tax credits, which include the federal and the state tax credits, τ_t, the household income level, I_t,[5] and the net present value of the system, S_t. The net present value of the system is the 25-year savings associated with solar electricity generation and depends on the electricity prices.[6] In addition, households have an idiosyncratic utility shock, ϵ_t, that is not observed by econometricians. Given the observed state-space $\Omega_t = \{C_t, \tau_t, I_t, S_t\}$ and the other unobserved state variable ϵ_t, each household decides each period whether to adopt a PV system or not. The discrete choice in time t is denoted by $d_t \in \{0, 1\}$, where d_t equals 1 represents the decision to adopt a residential PV system.

Assuming the per period utility, U, has an additively separable representation as in Rust (1988), it can be decomposed into two components:

$$U(\Omega, d, \epsilon, \gamma) = v(\Omega, d, \gamma) + \epsilon(d) \tag{1}$$

where $v(\Omega, d, \gamma)$ is the utility that a household receives from adopting a solar power system at state Ω and can be observed by econometricians, $\epsilon(d)$ is the random error term which is unobserved by econometricians, and γ is a vector of the parameters to be estimated.

[5]Household income level is a household characteristic. However, we include the income level, I_t, into the state space for the notational convenience.

[6]Even though project developers, long-term owners, and consultancies assume a 30-year or greater system lifespan Wiser et al. (2020), most solar panel manufacturers, such as LG, Sunpower, and Trina Solar, still offer a warranty of 25 years.

The utility that a household i receives from installing a PV system at time t can be expressed as:

$$v_{it}(\Omega_{it}, d_{it}; \boldsymbol{\gamma}) = \gamma_0 - \gamma_1(C_{it} - \tau_{it}) + \gamma_2 S_{it} \tag{2}$$

We also assume that the states evolve stochastically by following a Markov process with probability density p, $Pr\{\Omega_{t+1}, \epsilon_{t+1}|\Omega_t, \epsilon_t, \Omega_{t-1}, \epsilon_{t-1}, ...\} = p\{\Omega_{t+1}, \epsilon_{t+1}|\Omega_t, \epsilon_t\}$. Hence, the household's decision problem is a Markovian decision problem on the state space with elements (Ω_t, ϵ_t). Given the current state (Ω_t, ϵ_t), the household makes a sequence of decisions to maximize the sum of expected discounted utility over an infinite horizon. The value function V_γ can be defined as

$$V_\gamma(\Omega_t, \boldsymbol{\epsilon_t}) = \max_{\{d_t\}_{t=0}^{\infty}} \mathbb{E}_{\Omega', \varepsilon'} \left[\sum_{t=0}^{\infty} \beta^t u\left(\boldsymbol{\Omega}_t, d_t, \boldsymbol{\epsilon}_t; \boldsymbol{\gamma}\right) \right] \tag{3}$$

The infinite horizon and the Markovian transition function assumptions imply that the optimal value function V_γ is a solution to the Bellman equation given by

$$V_\gamma(\Omega, \boldsymbol{\epsilon}) = \max_{d \in \{0,1\}} \left\{ \underbrace{v(\Omega, 1; \boldsymbol{\gamma}) + \epsilon(1)}_{\text{Adoption}}, \underbrace{\epsilon(0) + \beta \int_{\Omega'} \int_{e'} V_\theta\left(\Omega', \boldsymbol{\epsilon}'\right) p\left(\Omega', \boldsymbol{\epsilon}' \mid \Omega, \boldsymbol{\epsilon}\right) d\Omega' d\boldsymbol{\epsilon}'}_{\text{Not Adoption}} \right\} \tag{4}$$

where (Ω', ϵ') represent the next-period state variables. In the case of adoption, a household derives utility from installing a system, $v(\Omega, 1; \boldsymbol{\gamma})$, and receives an unobserved shock, $\epsilon(1)$, then exits the market. Conversely, if the household does not adopt, it receives an unobserved shock, $\epsilon(0)$, for the current period and the discounted value of retaining the option to adopt in future periods.

There are two key challenges for direct econometric implementation, as highlighted in the literature. First, if the chosen distribution for the unobservable ϵ_t is continuous with unbounded support, dimensionality issues arise because the optimal decision function is derived from the fixed-point solution of the Bellman equation. Second, the unknown function $\mathbb{E}V_\gamma$ is nonlinear in ϵ_t, requiring integration over ϵ_t to obtain choice probabilities, which will be defined later. To address these challenges, Rust (1987) proposed the following critical assumption:

Conditional Independence Assumption: The states evolve following a Markov process with probability density p:

$$p(\Omega', \epsilon' | \Omega, \epsilon) = p_\epsilon(\epsilon' | \Omega') p_\Omega(\Omega' | \Omega) \tag{5}$$

This assumption imposes two key restrictions on the state variables. First, Ω is a sufficient statistic for ϵ'. Second, the probability density of Ω' depends only on Ω and not on ϵ. Consequently, conditional on Ω, the unobserved state variables ϵ have no predictive power for future states Ω' and ϵ'. Hence, the expected future utility can be rewritten as:

$$\mathbb{E}V_\gamma(\Omega) = \int_{\Omega'} \int_{\epsilon'} V_\theta \left(\Omega', \boldsymbol{\epsilon}'\right) p_\epsilon(\epsilon' | \Omega') p_\Omega(\Omega' | \Omega) d\Omega' d\boldsymbol{\epsilon}' \tag{6}$$

The choice-specific value function is then expressed as:

$$v_\gamma(\boldsymbol{\Omega}, d) = \begin{cases} \gamma_0 - \gamma_1(C - \tau) + \gamma_2 S, & d = 1 \\ \beta(\mathbb{E}V_\gamma(\Omega)), & d = 0 \end{cases} \tag{7}$$

As previously mentioned, the net present value includes the discounted future benefits of the system once adopted. The Bellman equation 4 can be expressed as:

$$V_\gamma(\Omega) = \max_{d \in \{0,1\}} [v_\gamma(\Omega, d) + \epsilon(d)] \tag{8}$$

We assume that $p_\epsilon(\epsilon' \mid \Omega')$ follows a multivariate extreme value distribution. As a result, $\mathbb{E}V_\gamma(\Omega)$ is the unique solution to the following functional equation:

$$\mathbb{E}V_\gamma(\Omega) = \int_{\Omega'} log \left\{ \sum_{d \in \{0,1\}} exp(V_\gamma(\Omega)) \right\} p_\Omega(\Omega' | \Omega) d\Omega' \tag{9}$$

Moreover, we characterize the conditional choice probabilities by assuming that the random error term, ϵ, follows a type I extreme value distribution:

$$Pr(d | \Omega, \gamma) = \frac{exp\{v_\gamma(\Omega, d)\}}{exp\{v_\gamma(\Omega, 0)\} + exp\{v_\gamma(\Omega, 1)\}} \tag{10}$$

where $Pr(1|\Omega, \gamma)$ denotes the probability of adopting a PV system and $Pr(0|\Omega, \gamma)$ denotes the probability of not adopting.

Finally, we assume that households form expectations about the evolution of system costs and the net present value of the system. The evolution of the net present value of the system is driven by changes in electricity prices. We discuss the specification of households' belief formation regarding the evolution of state variables after introducing the data.

4 Data

There are two primary data sources used in this paper. The first data source is the Residential Equipment and Technology (RET) survey conducted in 2014 by the Salt River Project in Phoenix. Salt River Project is a public utility company whose service territory covers nearly all Phoenix metropolitan areas. The survey provides detailed information about the households' characteristics such as income, ethnicity of the household head, number of persons in the household, as well as information about the building attributes and appliances, including the square footage of the house and having a swimming pool for solar and non-solar customers. Table 1 reports the summary statistics of household and building characteristics for solar and non-solar homes. Solar customers are 22 percentage points more likely to have a single-family house and 21 percentage points more likely to have a swimming pool than non-solar customers. The number of people per solar home is higher, (2.72 people per solar home, compared to 2.39 people per non-solar home), and houses with a solar system are larger than those without a system, on average.

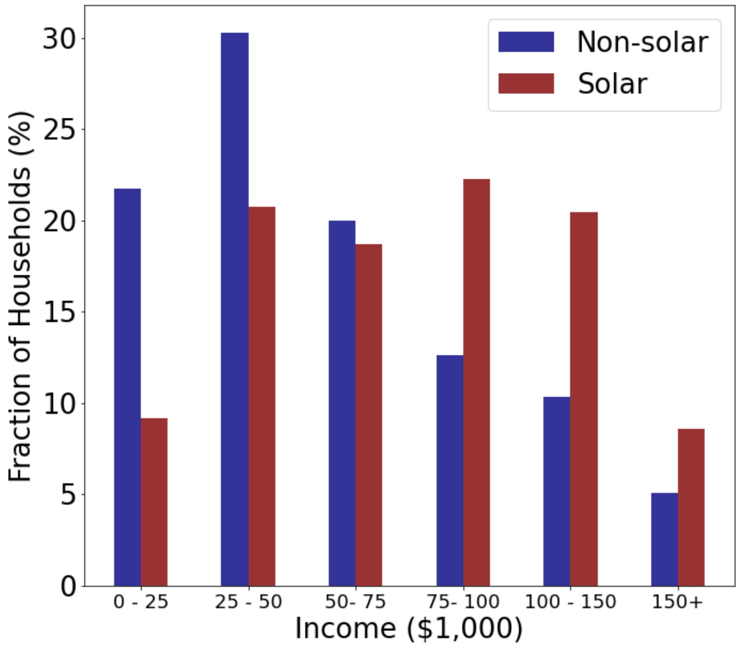
Table 1: Household and Building Characteristics

Variable	Mean	Std. Dev.	Min	Max	Obs.
Without Solar					
Square footage (1000 sqrft)	1.67	0.57	0.514	6.72	8,316
Number of persons in the household	2.39	1.55	1	9	10,511
Household head being white	0.73	0.44	0	1	11,252
Having a swimming pool	0.24	0.43	0	1	11,425
Single family house	0.77	0.42	0	1	11,055
With Solar					
Square footage (1000 sqrft)	2.13	0.82	0.95	8.09	251
Number of persons in the household	2.72	1.61	1	9	310
Household head being white	0.77	0.42	0	1	332
Having a swimming pool	0.45	0.49	0	1	337
Single family house	0.99	0.10	0	1	330

Note: The sample is restricted to households with income information from the Residential Equipment and Technology (RET) survey conducted by the Salt River Project in the Phoenix Metropolitan Area in 2014.

Figure 3 illustrates the fraction of households across income brackets for homes with and without solar systems. Households with income levels below $50,000 account for more than 50% of non-solar homes, whereas households with income levels above $50,000 comprise 70% of solar homes.

Figure 3: Fraction of Households Across Income Brackets for Solar and Non-Solar Customers



Note: The figure shows the fraction of households across income brackets for solar and non-solar customers. Household income is reported in $1,000.

The other dataset from the SRP contains information about hourly electricity consumption from 2013 to 2017 for each household that completed the RET Survey. Table 2 shows the summary statistics of electricity consumption for solar and non-solar homes. Even though the average daily electricity consumption of the solar customers is higher than that of the non-solar customers, the solar customers' average daily electricity purchase from the grid is less than half of the non-solar customers' electricity purchase from the grid. Moreover, solar customers pay less per kWh on average than non-solar customers. This evidence points to the relevance of the equity aspect of net metering. Figure 3 also shows that households with solar are disproportionately wealthy. So, when a customer installs solar, their share of the fixed costs are shifted to other ratepayers who earn less on average.

In addition, the dataset includes information on solar systems, such as hourly electricity generation, installation dates, adoption costs, and system sizes. Table 3 summarizes the characteristics of these systems. The average system size is 6.60 kW AC, with a mean adoption cost of $35,050, ranging from $6,197 to $115,790. Average annual savings from the systems amount to $1,145, while daily electricity generation averages 31.66 kWh.

Table 4 report households' characteristics by household income brackets. The data provides

Table 2: Electricity Usage Characteristics

Variable	Mean	Std. Dev.	Min	Max	Obs.
No Solar					
Average electricity price ($/kWh)	0.099	0.044	0.07	0.12	14,547,779
All year_daily electricity consumption (kWh/day)	36.73	24.70	0	708.56	14,547,779
Summer_daily electricity consumption (kWh/day)	46.78	26.87	0	708.56	7,460,432
Winter_daily electricity consumption (kWh/day)	26.17	16.53	0	448.96	7,087,347
With Solar					
Average electricity price ($/kWh)	0.093	0.01	0.05	0.11	347,986
All year_daily electricity consumption (kWh/day)	45.69	29.51	2	228.31	347,986
Summer_daily electricity consumption (kWh/day)	58.57	32.23	2	228.31	170,210
Winter_daily electricity consumption (kWh/day)	33.36	19.98	2	224.44	177,776
All year_net electricity purchase from the grid (kWh/day)	14.03	26.93	-53	202.00	347,986
Summer_net electricity purchase from the grid (kWh/day)	23.10	29.35	-53	202	170,210
Winter_net electricity purchase from the grid (kWh/day)	5.35	20.99	-53	173	117,776

Note: The sample is restricted to households who have income information in the Residential Equipment and Technology Survey, 2014, and are observed at least 15-day for each month.

Table 3: Solar System Characteristics

Variable	Mean	Std. Dev.	Min	Max	Obs.
System size (kW AC)	6.60	2.85	1.14	22	337
System size (kW DC)	7.49	3.57	1.38	25.5	337
Cost ($)	35,050	16,026	6,197	115,790	337
Installation year	2013.05	1.72	2009	2016	337
Average annual savings from the system ($)	1,145	538.11	177.30	4,543	377
All year_daily solar electricity generation (kWh)	31.66	17.92	0	158.74	347,986
Summer_daily solar electricity generation (kWh)	35.47	18.47	0	158.74	170,210
Winter_daily solar electricity generation (kWh)	28.01	16.60	0	158.15	177,776

Note: The sample is restricted to households with income information in the Residential Equipment and Technology Survey, 2014.

evidence that high-income households are more likely to install a solar system. The percentage of solar adopters monotonically increases with household income level. In addition, high-income households are more likely to have a single-family home and to have larger houses. These two characteristics provide incentives to adopt a solar system. If a household in an apartment wants to adopt a system, this requires coordination with other households living in the same building. Having a larger house implies having a larger rooftop space for solar systems so that households can install larger systems and decrease their marginal cost because of the economies of scale. Also, high-income households consume more electricity from the grid on average. Therefore, they can save more in the case of adoption.

The second data source is the Distributed Solar Public Data from Lawrence Berkeley National Laboratory's Tracking the Sun 2020 Database. LBNL publishes non-confidential project-level data on residential photovoltaic systems. The data set includes the total installed price for the system, the installation date, the system size, zip code, customer segment, and other

Table 4: Electricity Consumption and Household Characteristics across Income Brackets

Variables	Household Income Brackets	1^{st} <25K	2^{nd} 25K - 50K	3^{rd} 50K - 75K	4^{th} 75K-100K	5^{th} 100K-150K
Daily electricity consumption from the grid(kWh)						
Mean		29.42	33.75	36.96	40.64	44.43
Standard Deviation		12.79	13.72	14.12	14.96	15.77
Single Family Home (%)		0.68	0.74	0.79	0.86	0.91
Square footage (1000 sqrft)		1.40	1.55	1.68	1.88	2.05
Number of persons in the household		2.10	2.32	2.49	2.60	2.78
Household head being white (%)		0.67	0.71	0.74	0.78	0.81
Having a swimming pool (%)		0.13	0.18	0.25	0.32	0.45
Solar System Owner (%)		0.011	0.019	0.026	0.045	0.046
N of observations		2,526	3,547	2,358	1,523	1,254

Note: The sample is restricted to households with income information. Source: 2014 Residential Equipment and Technology Survey by Salt River Project.

system features. Arizona Public Service and Salt River Project are the data providers for the Phoenix metropolitan area. In order to maintain consistency between data sets, we restrict the sample to the 86 zip codes reported in the SRP Survey between 2009 and 2019. we also trim the top 1% and bottom 1% of the cost distribution to exclude outlier observations. Table 5 reports the summary statistics for the sample.

Table 5: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
Total cost of system	32,215	14,552	7,550	90,090	30,758
System size (kw DC)	7.46	3.39	0.215	24.96	30,758
Installation Year	2015.17	2,83	2009	2019	30,758

Note: The data source is the Distributed Solar Public Data. The sample includes project-level observations on residential solar system installations from 86 zip codes reported in the SRP Survey from 2009 to 2019.

Finally, the model requires information on the counterfactual value of adopting for each non-solar home. Since we cannot observe the adoption case for these homes, we estimate the expected system size, the expected cost of the system, the yearly savings from electricity generated by the system, and the expected tax credits that households would get if they were to adopt. This paper is the first to construct the value of adopting for each household in the literature focusing on the U.S. solar panel market.[7]

[7] Burr (2016) uses the average size system in the zip codes from California to calculate the value of adopting for non-solar customers. Langer and Lemoine (2018) also focuses on the median size of the system in the households' zip codes. Snashall-Woodhams (2019) assembles a rich data set with the support of the Google Sunroof Project for California homes; however, the data set in the paper does not provide information on the household income level, so the effect of income on the adoption is beyond the scope of his paper.

Constructing the Value of Solar System Adoption for Non-Solar Homes

First, we estimated the system size, as other variables depend on it. The method used to estimate the expected system size relies on the average daily electricity consumption, the average daily solar irradiation rate in the area, the average efficiency factor of modules, and the inverter loading ratio.[8] We validated our estimates by comparing the system size for non-solar homes with data from the Lawrence Berkeley National Lab (LBNL) Database, restricting the sample to systems installed after 2013.[9]

The next step is to estimate the expected installation cost for non-solar homes. To recover the average cost per kW in each zip code, as reported in the 2014 survey, we estimate a flexible, functional form of the average cost per kW.[10] The expected total installation cost is then calculated using the estimated system size (kW DC) and the average cost per kW for the household's zip code in 2014. Additionally, we calculate the annual savings from the system based on the average price per kWh observed by households and the expected annual electricity production of the system (kWh).[11]

Table 6 presents descriptive statistics for the estimated variables alongside data from the Lawrence Berkeley National Lab Database. The results show that the estimated system size and adoption costs closely align with the historical data.

Table 6: Comparison of Estimated System Variables with LBNL Data

		Mean	Std. Dev	Min	Max	# of obs.
PV System Size (kW DC)						
	LBNL	7.88	3.40	0.79	21.67	13,318
	Estimated Data	7.63	3.23	0.99	20.89	11,480
System Cost ($)						
	LBNL	33,654	15,296	7,314	86,430	13,318
	Estimated Data	33,812	15,335	3,448	96,805	11,480
Annual savings from system ($)						
	Estimated Data	1,145	481.27	144.48	3,032.58	11,480

Note: This table compares estimated system variables, including PV system size, system cost, and annual savings, with historical data from the Lawrence Berkeley National Lab (LBNL) Database. The LBNL sample is restricted to residential solar system installations from 86 zip codes reported in the 2014 RET Survey.

The final component of constructing the counterfactual values involves determining the tax credit a household would receive upon adopting a solar system. We consider two tax credits

[8] See Appendix A for a detailed explanation of the formulae, method, and calibrated parameters.

[9] Figure 5 in Appendix A presents a comparison of the distribution of estimated system sizes derived from our method with those from the LBNL sample. The results indicate that both the mean and the distribution of the estimated system sizes closely align with historical data.

[10] The estimation method for a flexible functional form is explained in detail in Household Beliefs and State Space, Equation 18.

[11] See Appendix A.

discussed in the Background section. The amount of tax credit depends on the household's tax liability. However, the dataset has two limitations. First, household income levels are reported as categorical variables. Second, the survey does not include information on marital status. These limitations prevent us from calculating the exact tax credit for a specific household.

To address these challenges, we use the weighted average tax rate for each income category based on the IRS 2014 report, which provides the number of households in different income brackets by marital status IRS (2014).[12] Using this approach, we calculate the average tax credit ratio for each income bracket. Since higher-income households are subject to higher marginal tax rates, households earning more than $50,000 are more likely to qualify for the full tax credit compared to those earning less.[13]

5 Estimation strategy

We use the nested fixed-point algorithm to estimate structural parameters in the model. The algorithm consists of an outer loop and an inner loop. It searches over the parameter space in the outer-loop to find the parameter values that maximize the log-likelihood function.

The log-likelihood function can be characterized as:

$$\max_{\gamma} \sum_{t=0}^{\infty} \sum_{i=1}^{N} [(d_t^i) log Pr(d_t^i = 1 | \Omega_t^i; \gamma) + (1 - d_t^i) log Pr(d_t^i = 0 | \Omega_t^i; \gamma)] \tag{11}$$

where Ω denotes the state space which consists of the cost of adoption, household income, the tax credits, and the net present value of the system observed by households, γ represents the parameters, and d denotes the choice of installing a solar panel. We can rewrite the log-likelihood function by plugging the choice-specific functions (7) and the conditional choice probabilities (10) into equation (11):

$$\begin{aligned} \max_{\gamma} \sum_{t=0}^{\infty} \sum_{i=1}^{N} \Bigg\{ & \left[(d_t^i) log \left(\frac{exp\{v_\gamma(\Omega, 1\}}{exp\{v_\gamma(\Omega, 1\} + exp\{\beta(\mathbb{E}V_\gamma(\Omega))\}} \right) \right] \\ + & \left[(1 - d_t^i) log \left(\frac{exp\{\beta(\mathbb{E}V_\gamma(\Omega))\}}{exp\{v_\gamma(\Omega, 1\} + exp\{\beta(\mathbb{E}V_\gamma(\Omega))\}} \right) \right] \Bigg\} \end{aligned} \tag{12}$$

In the inner loop, the algorithm uses value function iteration to solve for the fixed-point

[12] See SOI Tax Stats, Table 1.2, 2014.

[13] See Appendix A. Table 11 presents the estimated average tax credit ratios for different household income brackets.

of $\mathbb{E}V_\gamma(\Omega)$, for a given γ. Let $\mathbb{E}V_\gamma^\eta(\Omega)$ denote the numerical value during the η^{th} iteration. To iterate the value function, we start with an initial guess $\mathbb{E}V_\gamma^0(\Omega) = 0$ at $\eta = 0$. Then, we calculate $\mathbb{E}V_\gamma^\eta(\Omega)$ by using equation (9) and the initial guess as:

$$\mathbb{E}V_\gamma^\eta(\Omega) = T.ln(\sum_{d\in\{0,1\}} exp\{v(\Omega', d; \gamma) + \beta\mathbb{E}V_\gamma^{\eta-1}(\Omega)\}) \quad \text{for } \eta = 1, 2, 3, ... \tag{13}$$

where T is the state transition matrix. The algorithm repeats the iteration until the convergence criterion is satisfied in the inner loop.[14] If the convergence criterion is satisfied, it interpolates the fixed point, $\mathbb{E}V_\gamma^\eta(\Omega)$, then calculates the conditional choice probabilities. [15]

We specify the utility that a household receives from installing a PV system as:

$$v_\gamma(\mathbf{\Omega}, 1) = \gamma_0 - \gamma_1(Cost - \tau) + \gamma_2 Savings \tag{15}$$

where *Cost* denotes the total installed price of the system, τ denotes the tax credits. *Savings* is the net present value of the system, which is defined as discounted value of the annual savings generated from the system over 25 years:

$$S_t = \sum_{t=1}^{25}[\beta^{t-1}(1-\delta^s)^{t-1}(1+r^e)^{t-1}s_t] \quad \text{and} \quad s_t = p_t^e \sum_{m=1}^{365} q_m \tag{16}$$

where β is the discount rate, δ^s is the model degrade factor, r^e is the escalation rate for electricity prices, and s_t denotes the annual savings generated from the system which, in turn, depends on the price of electricity, p_t^e, and the daily electricity generated by the system, q_m.[16]

In another specification, we also let households' sensitivity to the cost of adoption vary across income brackets to identify the effect of income on adoption:

$$v_{it}(\mathbf{\Omega}, 1; \gamma, \lambda) = \gamma_0 - \gamma_1(Cost_{it} - \tau_{it}) + \gamma_2 Savings_{it} + \sum_{n=2}^{5} \lambda_i(Cost_{it} - \tau_{it}) * income_i \tag{17}$$

The parameter γ_1 measures households' sensitivity to the net cost of adoption, and γ_2

[14]The convergence criterion is

$$\sup_{\Omega} |\mathbb{E}V_\gamma^\eta(\Omega) - \mathbb{E}V_\gamma^{\eta-1}(\Omega)| < 1e-6 \tag{14}$$

[15]Following Burr (2016), we use the maximum likelihood estimation with the multistart algorithm of MATLAB in the outer loop. The multistart algorithm starts the local solver, *fminunc*, from multiple randomly selected start points and finds the parameter combinations that yield the highest likelihood value.

[16]Burr (2016) uses the solar radiation data for each zip code, and Reddix (2015) also uses the average hours of sunlight a household receives to calculate the net present value. Since we observe the actual electricity data and the electricity price, we can get a more accurate estimate of the net present value of the system.

measures households' sensitivity to the net present value of the system. The parameters λ_i captures how households' sensitivity to the net cost changes with the income bracket i.

5.1 Household Beliefs and State Space

The other important step in the estimation strategy is to specify how households form beliefs about the evolution of the state variables. In the model, households are assumed to be forward-looking and to have rational expectations over the evolution of solar system costs. We assume that the system costs evolve exogenously and follow a first-order Markov process. Moreover, we also assume that households have perfect foresight over changes in the electricity prices and changes in the incentive programs.

We use the Rouwenhorst (1995) method to construct the transition matrix and state space for the system cost variable. The data used in this stage comes from Lawrence Berkeley National Laboratory's Distributed Solar Public Data, summarized in Table 5. First, we recover the cost of the average size system in each zip code from 2009 to 2019 by assuming a flexible cost function to generate a panel data set. We assume that the cost of the system i in the zip code z at year t, C_{izt}, is a function of the system size (in kilo-Watts), x_i, the square of the system size, x_i^2, zipcode z, and year t;

$$C_{izt} = f\{x, x^2, z, t\} \tag{18}$$

Then, we predicted the cost of an average size system in each zip code for each year by using the estimated parameters. Hence, we generate a dynamic panel data set that includes the cost of the average size system for each zip code over the years. Then, we specify the cost function as:

$$C_{z(t+1)} = \alpha + \rho C_{z(t)} + \mu_z + \omega_{zt} \tag{19}$$

where ω is normally distributed, $\omega \sim \mathcal{N}(\mu,\, \sigma_\omega^2)$. $C_{z(t+1)}$ denotes the cost of the average size system in zip code z at time *t+1*, μ_z denotes the zip-code fixed effect, and ω_{zt} is the error term. For the Rouwenhorst (1995) method, we need to estimate ρ and σ_ω. We use the Arellano and Bond (1991) GMM estimator to estimate ρ and σ_ω.[17] The estimate of ρ is 0.925, and of σ_ω is 1.8434. Langer and Lemoine (2018) estimated that ρ equals 0.9925 and σ_ω equals 0.1611 using the average per-Watt installed system price each month.

As previously mentioned, we use the method proposed by Rouwenhorst (1995) to construct

[17] See Appendix B for the detailed explanation.

the transition matrix and the state space for the cost variable. The average cost per watt, \$4.31, is used in this construction. The grid space is discretized into 80 points, ensuring that the minimum and maximum cost values are included. To complete the state space, we calculate the net present value (NPV) of the system using Equation 16.

We assume a constant degradation factor, $\delta^s = 0.5\%$, over the study period, based on the Google Sunroof Project. Future changes in electricity prices are specified using SRP rate books from 2013 to 2019.[18] According to these rate books, the nominal utility escalation rate averages 2%, which we assume remains constant. Additionally, the price of electricity for each plan in year t is taken directly from the rate books.

Lastly, we assume households discount future income at a rate of $\beta = 0.878$, as estimated by De Groote and Verboven (2019). Using the estimated minimum and maximum values of the net present value, we discretize the savings grid accordingly.

6 Model Results and Fit

6.1 Model Results

Table 7 reports the result of the estimated coefficients. The final sample is restricted to households that own single-family homes. We also limited the sample to houses with an actual or estimated system size larger than 2 kW DC. Finally, we drop 5% of households with income level higher than \$150,000 since there is no upper bound reported for this income bracket.[19]

Column (1) reports the parameter estimates where the specification only includes the net cost of adoption and the net present value of the system without allowing heterogeneity across income brackets. In column (2), we let households' sensitivity to the net cost of adopting a system vary across income brackets.

All coefficients have the expected signs. First, the average household has a negative valuation of the solar system and households get disutility from the net cost of adoption. Furthermore, the coefficients of the interaction of cost and income brackets mean that the household's sensitivity to the cost of adoption decreases as income increases. Specifically, the coefficient of the net cost for households who earn between \$50,000 - \$75,000 equals -0.375 and gradually diminishes for higher-income households, being around -0.223 for households who earn between \$100,000 -

[18] SRP publishes rate books detailing charges for each rate plan.

[19] 78% of households in the data have a single-family home, and 95% of households report income level below \$150,000. Moreover, 1% of the system size is below 2 kW DC.

Table 7: Solar System Adoption Model Estimates

		(1)	(2)
Constant		-4.214***	-3.911***
		(0.187)	(0.197)
Net Cost ($10,000)		-0.486 ***	-0.580***
		(0.133)	(0.153)
Savings ($10,000)		1.233 ***	0.640*
		(0.345)	(0.384)
Fixed Interactions with Cost			
Category 2 -	$25,000 - $49,999		0.130
			(0.103)
Category 3 -	$50,000 - $74,999		0.205***
			(0.104)
Category 4 -	$75,000 - $99,999		0.328***
			(0.104)
Category 5 -	$100,000 - $149,999		0.357***
			(0.103)
N Obs		16,321	16,321

Note: Bootstrapped standard errors reported in parentheses. The sample is restricted to households with single-family houses and earning less than $150,000. Also, we restricted the sample to an actual or estimated system size larger than 2 kW DC. The net cost of adoption and the net present value of savings are measured at $10,000.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$150,000. We also find that the savings from the system increase households' utility from the system. The estimated coefficients suggest that a $1 increase in the savings from the system weighs slightly more than a $1 decrease in the net cost of adoption. This result is not consistent with some of the findings in the literature. Studies focusing on California and Switzerland report that households value the decrease in the cost more than the increase in the savings. Possible explanations for these differences could be that the median size of the system is higher in Arizona, whereas the cost per watt is lower. Hence, the unit cost of the system is relatively smaller. Also, Arizona has a higher solar irradiation rate than these places, and the same size system will cost less and produce more electricity compared to California and Switzerland.

6.2 Model Fit

Table 8 compares the targeted and untargeted moments from the data with their model counterparts. Panel (A) displays the distribution of solar panel adoption rates across income quantiles, which are the targeted moments. The model performs well in replicating the adoption rates within individual income quantiles. Although the model best predicts adoption rates for the second and third income quantiles, it successfully captures the overall increasing trend in adoption rates across higher income groups.

Table 8: Targeted and Untargeted Moments

Panel A:Targeted Moments		
Income	Data (%)	Model (%)
<$25K	1.40	1.81
$25K-$50K	2.35	2.52
$50K -$75K	2.88	2.96
$75K-$100K	4.45	4.01
$100K-$150K	4.98	4.35
Panel B:Untargeted Moments		
Year	Data (%)	Model (%)
2013	0.8	0.94
2014	1.1	0.99
2015	1.2	1.07

Note: Panel A reports targeted moments, showing the income distribution in both the data and the model. Panel B reports untargeted moments, focusing on the year-specific distribution. Percentages are rounded to two decimal places.

Panel (B) reports the untargeted moments, tracking annual solar adoption rates over time. While these moments were not directly calibrated, the model closely replicated the observed trends and levels in the data. This consistency highlights the model's ability to capture key adoption dynamics, even for patterns not explicitly targeted during calibration, which is crucial for reliable counterfactual analysis and policy evaluation.

7 Counterfactual Analysis

We conduct two counterfactual analyses while maintaining the ex-ante budget equivalent at the benchmark level.[20] The benchmark policy is a non-refundable federal tax credit scheme, which provides 30% of installation costs as a non-refundable tax credit. In the first counterfactual, we modify the scheme to make the tax credit refundable, allowing us to evaluate how the refundability of tax credits impacts the distribution of benefits among households. The second counterfactual examines an alternative refundable tax credit subsidy scheme inspired by the *Justice40* initiative.[21] This scheme is designed to allocate 40% of the total benefits to households with incomes below $50,000.

Column (1) in Table 9 presents the changes in solar adoption rates, total tax credits, and

[20] The implementation of these two counterfactuals is the same as giving upfront investment subsidies in the counterfactual design.

[21] See the White House for details on the Justice40 Initiative.

Table 9: Effects of Counterfactual Policies

	Refundable Tax Credit	Alternative Scheme
Change in Solar Adoption Rate (%)		
<$25K	16.4	33.4
$25K-$50K	2.8	-
$50K -$75K	0.7	-
$75K-$100K	0	-3.4
$100K-$150K	0	-4.1
Change in Total Tax Credit (%)		
<$25K	47.0	168.4
$25K-$50K	6.5	-
$50K -$75K	1.45	-
$75K-$100K	-	-16.4
$100K-$150K	-	-20.3
Change in Solar Production (%)		
<$25K	17.9	40.1
$25K-$50K	2.45	-
$50K -$75K	0.35	-
$75K-$100K	-	-3.75
$100K-$150K	-	-4.45
Change in Total Solar Production	102.2	102.1

This table reports the changes in solar adoption rates, total tax credits, and solar production across income categories under counterfactual policies compared to the benchmark case. Column (1) presents the results of transitioning from a nonrefundable tax credit policy to a refundable one, while Column (2) shows the results for an alternative scheme designed to allocate 40% of total tax credits to households earning less than $50,000.

solar production across income categories under the refundable tax credit scheme compared to the benchmark case. Making nonrefundable tax credits refundable substantially increases the solar adoption rate among low-income households, with no notable changes in adoption for higher-income groups ($> \$75K$). The adoption rate increases most significantly for households earning less than $25K, with a rise of 16.4%, followed by smaller gains for the $25K–$50K and $50K–$75K groups, at 2.8% and 0.7%, respectively. These findings demonstrate that low-income households are unable to fully benefit from nonrefundable tax credit policies due to their low tax liability. Implementing such policies exacerbates solar adoption inequities between high- and low-income households. While the gross cost of installing a system of the same size is identical for both groups, high-income households incur a lower net cost.

Similarly, the total tax credits received by low-income households increase by 47%. This change is driven by two factors: first, households already adopting solar systems now receive higher benefits; second, marginal households changed their decision in favor of adopting a system because the tax credit made it more financially viable. Middle-income groups experience modest benefits, with increases of 6.5% for the $25K–$50K bracket and 1.45% for the $50K–$75K bracket, while higher-income groups ($75K–$150K) see no changes.

The change in marginal households among low-income groups is reflected in the increase in solar production by 17.9%. There are small increases in solar production for the $25K–$50K income group (+2.45%) and the $50K–$75K income group (+0.35%), with no changes for higher-income groups. Overall, transitioning from a nonrefundable to a refundable tax credit policy increases total solar production by 102.2%.

In the second counterfactual analysis, we aim to allocate 40% of the total benefits to households with incomes below $50,000, inspired by the *Justice40* Initiative. Under this scenario, the scheme is designed to cover 40% of the total system cost for the first income bracket, 30% for the second and third income brackets, and 25% for the highest two income brackets. This change results in a 168.4% increase in total tax credits received by low-income households at a cost to higher-income households. The total tax credits received by households with incomes between $75K and $100K decrease by 16.4%, while those with incomes above $100K experience a reduction of 20.3%.

Although solar production declines by 3.75% for households earning between $75,000 and $100,000, and by 4.45% for those earning between $100,000 and $150,000, it increases by 40% for low-income households. This substantial increase is sufficient to maintain total solar production at the same level as the refundable tax credit scenario while still showing an improvement compared to the benchmark case. The main mechanism behind these findings is that high-income households are less responsive to changes in net cost. As a result, even when net costs increase, only a small fraction of them alter their solar adoption decisions. In contrast, low-income households are highly sensitive to the net cost of the system. Therefore, a decrease in net cost incentivizes marginal households to adopt the system. Our results show that the *Justice40* Initiative can achieve a more pronounced redistribution of benefits toward lower-income households without compromising efficiency.

8 Conclusion

In this paper, we develop a dynamic demand model for residential solar PV systems. The model evaluates the effects of adoption costs, household income, tax credits, and savings from system electricity generation on preferences for rooftop solar systems. We estimate the model using a novel, rich household-level dataset from the Phoenix Metropolitan area. Our findings reveal that household sensitivity to adoption costs decreases as income increases. Additionally, we find that a \$1 increase in savings from the system weighs slightly more than a \$1 decrease in the net cost of adoption.

We then use the model to conduct two counterfactual analyses, documenting the distributional effects of nonrefundable tax credit policies. Our analysis highlights significant distributional and efficiency effects of transitioning from nonrefundable to refundable tax credit policies for solar adoption. Under the refundable tax credit scheme, solar adoption rates increase substantially among low-income households, with no notable changes for higher-income groups ($\geq$ \$75K). The adoption rate rises by 16.4% for households earning less than \$25K, with smaller increases for middle-income groups and no change in higher-income groups. This change addresses a fundamental limitation of nonrefundable tax credits: low-income households' inability to fully benefit due to low tax liabilities, which contributes to inequities in solar adoption. Transitioning to a refundable tax credit increases total solar production by 102.2%, driven by a 17.9% rise in solar production because of marginal households among low-income households.

The second counterfactual analysis, inspired by the *Justice40* Initiative, redistributes 40% of total benefits to households earning less than \$50,000. This scheme increases total tax credits received by the lowest income brackets by 168.4%, at a cost to higher-income households. Despite these declines, solar production among low-income households rises by 40%, offsetting decreases for higher-income groups and maintaining total solar production at the same level as the refundable tax credit scenario. These results emphasize that high-income households are less responsive to changes in net costs, whereas low-income households are highly sensitive, with reductions in net costs significantly incentivizing adoption. The *Justice40* Initiative demonstrates its potential to redistribute benefits toward lower-income households more effectively while maintaining overall efficiency, offering a pathway to address equity concerns in solar adoption.

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Appendix A

A solar PV system converts the energy in sunlight into direct current (DC) electricity. Then an inverter converts DC electricity into alternating current (AC) electricity used for appliances at a house. So, the system size would be installed in a home depending on several factors such as average daily electricity usage, the climate and the amount of sunlight in the area, the efficiency of the solar panels, and the efficiency of the inverter. After We searched over the different calculation methods for the system size, We estimated the non-solar homes' system size by following the steps below.

The first thing that needs to be recovered is the average daily electricity consumption for each household. Since the hourly electricity consumption data is unbalanced and has missing days for households, We restricted the sample to the households observed at least 15 days in each month. Then, We checked how the monthly and yearly electricity consumption changes over the years to understand whether there is a trend. Figure 5 shows the average electricity consumption from the grid (kWh) for each month from 2014 to 2016.

Figure 4: The figure shows the average electricity consumption from the grid (kWh) for each month from 2014 to 2016. Source: Salt River Project

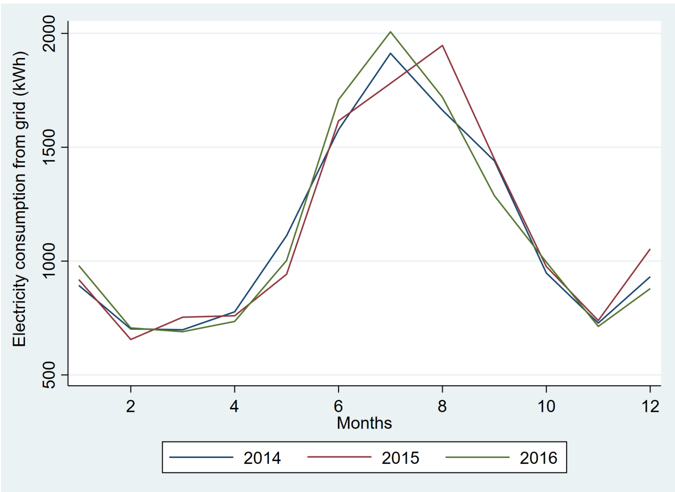


Table 8 reports the average monthly consumption for each month from 2014 to 2016. Then, We aggregated the monthly consumption to the yearly consumption. Even though the average electricity consumption for each month changes over the years, there is no trend in the annual electricity consumption. In addition, the average monthly consumption, which equals the yearly consumption is divided by 12, is very similar over the years. The average monthly consumption is very close to 1,061 kWh per month, the number reported by the U.S. Energy Information Administration.

Table 10: Average Electricity Consumption (kWh)

	Average Electricity Consumption (kWh)		
Months	2014	2015	2016
January	893.343	918.9305	980.217
February	702.1748	655.7467	706.3784
March	698.4245	753.6331	690.0547
April	777.267	759.9178	734.9548
May	1,111.578	942.2171	1,002.636
June	1,577.162	1,615.926	1,708.616
July	1,912.528	1,780.428	2,007.193
August	1,662.576	1,946.992	1,719.796
September	1,440.292	1,448.122	1,287.265
October	947.6654	976.0956	995.6488
November	727.9626	739.0054	713.056
December	931.4877	1053.506	879.1697
Yearly consumption	13,382.46	13,590.52	13,424.99
Average monthly consumption	1,115.205	1,132.543	1,118.749
# of Observations	97,680	97,680	97,680

We continued by finding the average daily consumption for each month to recover the average daily consumption for each household. Then, We aggregated the monthly consumption to the yearly consumption in kWh. Finally, we divided the yearly consumption by 365 to determine each household's average daily consumption (kWh). The method of estimating the expected system size uses the average daily electricity consumption, sun-peak hours in the area, the average efficiency factor of modules, and the inverter loading ratio. **The efficiency factor of module** is the ability of the panel to convert sunlight into usable energy. **Sun-peak hours** describes the intensity of sunlight in a specific area and is defined as an hour of sunlight that reaches, on average, 1,000 Watts of poWe r per square meter. **The inverter loading ratio** is the ratio of DC module capacity to AC inverter capacity.

The first step of the method is to calculate how much daily electricity generation a household needs from the solar system to meet their average daily electricity consumption (kWh). The implicit assumption is that households choose the system size to compensate for their average daily electricity consumption. Even though the system produces energy only in daylight, the excess energy can be delivered back to the grid to offset the usage from the grid because of the net metering policy.

$$\textit{The daily energy need} = \textit{Average daily electricity consumption * the efficiency of the module}$$

The second step is to calculate the power to be supplied to the inverter by using the inverter loading ratio:

The daily power to be supplied to the inverter = *The daily energy need / The inverter loading ratio*

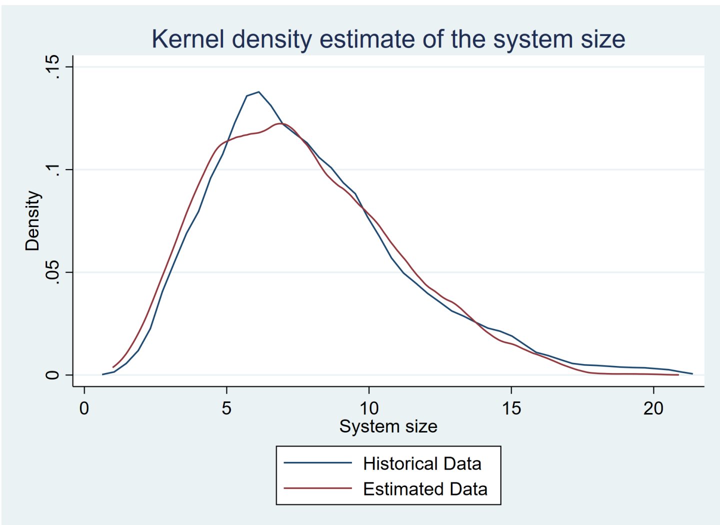
The final step is to calculate the system size to produce the daily power by using the average daily sun-peak hours:

The system size (kW DC) = *The daily power / the average daily sun-peak hours*

We assume that the module's efficiency is 15.3% and the inverter loading ratio is 0.85, following the Google Sunroof Project. We also assume that Phoenix has an average annual solar radiation value of 6.58 kilowatt hours per square meter per day (kWh/m2/day) using the NREL Database.

We validated our estimates by comparing the system size for non-solar homes with data from the Lawrence Berkeley National Lab (LBNL) Database, restricting the sample to systems installed after 2013. Figure 5 presents a comparison of the distribution of estimated system sizes derived from our method with those from the LBNL sample. The results indicate that both the mean and the distribution of the estimated system sizes closely align with historical data.

Figure 5: Comparison of the distribution of system sizes reported in the LBNL sample and those estimated by the method.



The other part of the value of adoption is the expected net present value of the system, which is defined as a discounted value of the annual savings generated from the system over 25 years.

The average price per kWh and how much the system produces in a year are two necessary variables to estimate the expected yearly savings from the system's electricity generation. There are two parts of savings from solar generation. It decreases electricity consumption from the grid, especially on-peak hours, Also, any system-generated excess energy is delivered back to the grid. Even though the system generates electricity on peak hours, We will assume that households calculate their expected savings by using the average price per kWh they observe in their bills following Ito (2014). The annual savings from the system can be described as

$$\textit{Average price per kWh * Estimated amount of electricity (kWh) per year}$$

The estimated amount of electricity (kWh) generated by a system per year can be calculated as

$$\textit{Production ratio * System size in Watts}$$

where **the production ratio** is the estimated amount of kWh per year a solar system will produce, divided by the total wattage of the solar system. The mean production ratio for solar homes equals 1.5 in the data set.

Table 11 reports the ratio of how much tax credit a household could receive on average for each income bracket.

Table 11: Estimated average tax credit ratio

	Estimated average tax credit ratio
Household Income	
\$0 - \$24,999	0.706
\$25,000 -\$49,999	0.951
\$50,000 - \$74,999	0.992
\$75,000 - \$99,999	0.999
\$100,000 - \$149,999	1.000

Appendix B

We use the Arellano and Bond (1991) GMM estimator to estimate ρ and σ_ω. First, we apply the first difference transformation to eliminate fixed effects. However, taking the first differences creates a correlation between the regressor and the error term. To deal with this problem, we construct an instrument matrix that consists of the lagged values of the instrumented variable. The choice of instruments depends on the serial correlation of ω and the lagged values. If ω follows an AR(1) or AR(2) process, we can still use the lagged cost values by backing off periods.

One of the critical diagnostics in dynamic panel data estimation is the AR test for autocorrelation of the residuals. Table 10 shows the result of the Arellano-Bond test for AR(1), AR(2), and AR(3) in the first differences.

Table 12: Results of Arellona-Bond test

	Z-score	P-value
Arellano-Bond test		
AR(1)	-4.65	0.000
AR(2)	1.76	0.078
AR(3)	0.24	0.812

As Table 10 shows, there is strong evidence against the null hypothesis, which is that differenced residuals do not exhibit significant AR(1) behavior, and the result for AR(2) statistic is not significant at the 5% level. This confirms the absence of second-order serial autocorrelation in the errors (Labra and Torrecillas (2018)). The lags 3-6 are used in constructing the GMM instrumental matrix to address this problem. We also check the Sargan and the Hansen test to verify the validity of the instruments. The p-values obtained in the Sargan test are **0.410** and are **0.117** in the Hansen test. According to the results, we cannot reject the null hypothesis that the instruments used in the estimation are valid. Therefore, overidentification does not exist (Labra and Torrecillas (2018)).